Analyzing Short Term Corporate Credit Risk Indicators Based on User Generated Content During the Corona-Pandemic

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Abstract: During the Corona-Pandemic, information (e.g. from the analysis of balance sheets and payment behavior) traditionally used for corporate credit risk analysis became less valuable because it represents only past circumstances. Therefore, the use of currently published data from social media platforms, which have shown to contain valuable information regarding the financial stability of companies, should be evaluated. In this data e. g. additional information from disappointed employees or customers can be present. In order to analyze in how far this data can improve the information base for corporate credit risk assessment, Twitter data regarding the ten greatest insolvencies of German companies in 2020 and solvent counterparts is analyzed in this paper. The results from t-tests show, that sentiment before the insolvencies is significantly worse than in the comparison group which is in alignment with previously conducted research endeavors. Furthermore, companies can be classified as prospectively solvent or insolvent with up to 70% accuracy by applying the k-nearest-neighbor algorithm to monthly aggregated sentiment scores. No significant differences in the number of Tweets for both groups can be proven, which is in contrast to findings from studies which were conducted before the Corona-Pandemic. The results can be utilized by practitioners and scientists in order to improve decision support systems in the domain of corporate credit risk analysis. From a scientific point of view, the results show, that the information asymmetry between lenders and borrowers in credit relationships, which are principals and agents according to the principal-agent-theory, can be reduced based on user generated content from social media platforms. In future studies, it should be evaluated in how far the data can be integrated in established processes for credit decision making. Furthermore, additional social media platforms as well as samples of companies should be analyzed. Lastly, the authenticity of user generated contend should be taken into account in order to ensure, that credit decisions rely on truthful information only.

Keywords: Corporate Credit Risk, User Generated Content, Social Media

1. Introduction

The Corona-Pandemic had severe impact on risk assessment especially in the domain of corporate credit risk analysis. Due to politically imposed restriction for many business activities especially in branch stores, historical data (e. g. balance sheets and payment behavior), which is usually utilized in order to calculate credit ratings and credit default risks, could not be used in order to estimate the financial stability of many companies during the corona pandemic (Enria, 2020). The challenges caused by the limited information base for corporate credit risk assessment appeared in a period in which the uncertainty regarding the going concern of companies was high since the development of the corona-pandemic and the reactions by governments could hardly be predicted.

Previous research endeavors have shown, that especially textual user generated content (UGC) from social media platforms contains valuable short-term information, which can be used to assess the financial stability of companies (Kearney & Liu, 2014; Nassirtoussi et al., 2014). In this paper, social media platforms are defined as "a group of internet-based applications that build on the ideological and technological foundations of Web 2.0, and that allow the creation and exchange of User Generated Content" (Kaplan & Haenlein, 2010). Furthermore, UGC "can be seen as the sum of all ways in which people make use of social media" (Kaplan & Haenlein, 2010). Next to literature in which dependencies between textual UGC and prices of financial instruments are proven, the coherence of texts from social media platforms and insolvencies has been analyzed (Mengelkamp et al., 2015a).

We answer the following research question in this paper in order to contribute to the extension of the information base for corporate credit risk assessment in times with economic distortion:

In how far can textual UGC provide short-term information for corporate credit risk assessment during exceptional economic conditions?

From a theoretical perspective, the investigation of the research questions aims at reducing the information asymmetry between borrowers (principals) and lenders (agents) in credit transactions, which are one use case of the principal-agent-theory (Stiglitz, 1988; Stiglitz & Weiss, 1981).

2. Developing the research hypotheses

The explanatory power of the amount of UGC regarding financial figures and ratings of companies has been widely analyzed with varying results (Anderson, 1998; Bollen et al., 2011). In earlier literature, similar results could be obtained while analyzing news Hereby, it was discovered, that news with negative content are dominant because people tend to be more talkative when they are unsatisfied (Hall & Young, 1991; Kotler, 1991; Richins, 1987). Therefore, we want to analyze in how far these findings can be confirmed in extraordinary economic circumstances by investigating the research hypothesis:

***H1:** The amount of UGC during the corona-pandemic is greater before an insolvency of a company than for financially stable companies*

Furthermore, in many research endeavors it has been analyzed in how far sentiment (e. g. negative, neutral or positive) from textual UGC can be used to predict prices of financial instruments (e. g. stocks) or potential insolvencies (Bollen et al., 2011; Kearney & Liu, 2014; Mengelkamp et al., 2015a; Nassirtoussi et al., 2014). We evaluate in how far these insights can also be utilized to reduce the information asymmetry between lenders and borrowers in credit relationships during an economic crisis caused by public health emergencies by testing the second research hypothesis:

***H2:** The sentiment of UGC during the corona-pandemic is worse before an insolvency of a company than for financially stable companies*

Thirdly, it is necessary to be able to distinguish between potential solvent and insolvent companies in order to decide to which companies credit can be granted. Mengelkamp, Hobert and Schumann (2015a) have shown, that this is possible with up to 75 % accuracy when companies are classified as potentially solvent or insolvent while applying the k-nearest-neighbor algorithm onto monthly aggregated sentiment scores from UGC in the year before an insolvency. The distinguishing between solvent and insolvent companies based on UGC is of extraordinary relevance in uncertain periods of time with unfamiliar conditions because they can provide short term information and thus, improve the traditional data base used for corporate credit assessment. Thus, we evaluate the third research hypothesis:

***H3:** It is possible to distinguish between solvent and insolvent companies based on sentiment scores derived from textual UGC during the corona-pandemic*

3. Data base for hypotheses testing

We construct a data set for the testing of our hypothesis in accordance with Mengelkamp, Hobert and Schumann (2015a), who evaluated differences in amount, sentiment and classification results of UGC regarding the ten biggest German insolvencies in 2013 and a comparison group. Differing from previous studies we chose the ten biggest German insolvencies according to the number of employees who became unemployed in the year 2020, in which the corona-pandemic rose (German Federal Bureau of Statistics, 2021). The selection of German companies is suitable in this context because the governmental restriction during the corona-pandemic in Germany were among the strongest (Ritchie et al., 2022). We selected a solvent counterpart based on a discussion of the following criteria for each of the insolvent companies:

- Line of business
- Turnover
- Number of Employees
- Total Assets
- Form of Company

Then, we extracted all posts from the social media platform Twitter for the pairs of companies. We only selected Tweets in the German language, because the authors are capable of the German language and all companies are headquartered in Germany. The search terms were constructed through an iterative process in which we started with the full name of each company according to the German commercial register. Then, we successively shortened the name (e. g. regarding form of company) in order to also find Tweets which are related to the companies but do not include the full name. We stopped the shortening of the search terms if Tweets were selected, which are not related to the companies.

For each pair of companies, the Tweets, which were posted within three years before the date of insolvency from the bankrupt company, were extracted. We chose the time span of three years in order to be able to assess in how far the companies were financially unstable before the corona-pandemic. The resulting data set, which consists of 1009 Tweets is presented in Table 1.

Table 1: Data set consisting of Tweets regarding insolvent and solvent companies

Insolvent Companies			Solvent Companies	
Date of Insolvency	Company Name	Number of Tweets	Number of Tweets	Company Name
01.07.2020	Esprit Holding Limited	9	2	Street One CBR Fashion Holding GmbH
15.04.2020	Hallhuber GmbH	374	3	Jeans Fritz GmbH
09.06.2020	Bonita GmbH	121	15	Engelhorn GmbH & Co. KGaA
01.05.2020	ARWE Holding GmbH	5	16	Mr. Wash Autoservice AG
02.07.2020	KSM Casting Group GmbH	11	2	Druckgußwerk Wolf GmbH
09.12.2020	Clemens Kleine Holding GmbH	5	4	Stölting Service Group GmbH
01.04.2020	Galeria Kaufhof GmbH	72	231	Breuninger GmbH & Co. KG
28.07.2020	Veritas AG	29	16	ATU GmbH & Co. KG
30.11.2020	Klier Hair Group GmbH	79	11	Ryf Coiffeur GmbH
25.05.2020	Tria Personal GmbH	1	3	ZAG GmbH

4. Data Analysis

After the quantification of the textual data, we present descriptive findings. Then, quantitative statistics resulting from the testing of the hypotheses are discussed.

4.1 Quantification of the textual data

The Tweets are quantified by use of the methodological approach of content analysis which was introduced by Neuendorf (2002). The quantification is necessary in order to be able to test the hypotheses H2 and H3. Referring to Mengelkamp, Hobert and Schumann (2015a), we manually labelled the data because this procedure is most accurate especially in domains in which content analysis has not been widely applied yet. This approach is more accurate especially when compared to automated analysis (Stieglitz et al., 2014). We rely on the codebook which has already by used by Mengelkamp, Hobert and Schumann (2015a) and (2015b) and is based on the methodology of Neuendorf (2002). The codebook is depicted in

Table **2**.

Table 2: Codebook used for manual labelling of the Tweets (Mengelkamp et al., 2015a, 2015b; Neuendorf, 2002)

Score	Requirement
2	Tweet contains evidence concerning financial stability regarding the company
1	Tweet does not contain evidence of financial stability but sentiment is positive regarding the company
0	Tweet does not contain sentiment regarding the company or contains positive and negative sentiment
-1	Tweet does not contain evidence of financial instability but sentiment is negative regarding the company
-2	Tweet contains evidence concerning financial instability regarding the company

The labelling was performed by two coders independently from each other who achieved an intercoder reliability according to Neuendorf (2002) of 96,04%, which is above the threshold of 90% that is desirable so that the categories in the codebook can be considered as sufficiently different from each other. This means, that the assignment of sentiment scores to Tweets according to the codebook by the coders differed in only 40 (3,96%) of the 1009 Tweets. Referring to Neuendorf (2002), the 40 Tweets in which the coders did not achieve consensus were discussed and the final score used for the following analysis was determined.

Then, we summarized the Tweets and assigned sentiment scores for the group of insolvent respectively solvent companies. The result is shown in Table 3.

Table 3: Number of Tweets for insolvent and solvent companies in the sentiment categories

Score	Insolvent Companies	Solvent Companies
2	0 (0,0%)	4 (1,3%)
1	54 (7,6%)	30 (9,9%)
0	424 (60,1%)	269 (88,8%)

Score	Insolvent Companies	Solvent Companies
-1	113 (16,0%)	0 (0,0%)
-2	115 (16,3%)	0 (0,0%)
Sum	**706 (70,0%)**	**303 (30,0%)**

4.2 Descriptive overview of the data

In Table 3 it can be seen, that the number of Tweets for the insolvent companies is greater than for the group of solvent companies as it makes up 70,0% of the Tweets. This is a first indicator, that an increasing number of Tweets can be an indicator for financial instability, which supports similar findings from Mengelkamp, Hobert and Schumann (2015a). Another remarkable insight is the missing of negative Tweets in the group of solvent companies. Although Mengelkamp, Hobert and Schumann have shown in (2015a) as well as (2015b), that negative Tweets are sometimes posted with relationship to financially stable companies, our sample emphasizes, that negative postings can be an indicator for financial instability and should therefore be carefully analyzed. Furthermore, it is remarkable, that the number of neutral Tweets is even higher for both groups of companies when compared to the sample from Mengelkamp, Hobert and Schumann (2015a, 2015b). The authors reported 49,9% of neutral Tweets for insolvent companies and 79,4% for solvent companies whereby our values are above these measures with 60,1%, respectively 88,8%. An explanation for the increased number of neutral Tweets could be the longer timespan of three years in our study whereas Mengelkamp, Hobert and Schumann (2015a, 2015b) considered only one year before the insolvencies. The number of positive Tweets is low in accordance with the mentioned previous studies. All percentages in our study in these categories are even smaller which could also be caused by the expanded time span.

The frequency distribution of Tweets before an insolvency should therefore be further investigated in subsequent research endeavors in order to verify the added value for corporate credit decision making when considering the number of Tweets.

In the next step, we plotted graphs based on average monthly sentiment scores for each company. By doing so, we are able to uncover patterns in the trends of sentiment which are typical before an insolvency and can compare these with findings from Mengelkamp, Hobert and Schumann (2015a).

The insolvent company is represented by a drawn through line whereby the solvent counterpart is depicted by a dotted line:

Insolvent company: ———————   Solvent company: - - - - - - - - -

In Figure 1 the sentiment score before the insolvency of the Klier Hair Group GmbH and the solvent counterpart Ryf Coiffeur GmbH can be seen. Both companies are operating in the hair dresser industry and had to close their branches in Germany due to a lockdown imposed by the German government in order to contain the corona-virus (Schuetze, 2021). It is evident, that the sentiment for the Klier Hair Group GmbH begins to continually decrease eight months before the insolvency. At this point, disturbances within the company appeared as the management tried to resign members of the employee organization (DGB Hamburg, 2020). In the following months, the closing of branches was promoted and subsequently put into action until the filing for insolvency (Salzburg24, 2020).

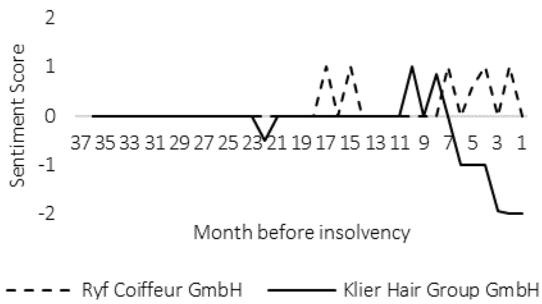

Figure 1: Monthly sentiment scores for Ryf Coiffeur GmbH and Klier Hair Group GmbH

The comparison of sentiment scores related to the Jeans Fritz GmbH with the insolvent Hallhuber GmbH, which are both operating in the clothing industry, shows similar results. The sentiment scores for the Hallhuber GmbH start to drop around 17 months before the insolvency, whereas the scores for the Jeans Fritz GmbH are continuously positive as depicted in Figure 2. The negative sentiment is mainly caused by reports about financial losses as well as speculations about the selling of the company due to financial difficulties of the parent company (Radio Gütersloh, 2019). The positive sentiment regarding the Jeans Fritz GmbH is caused by a Tweet in which a customer praises the clothes of that company (Burgaupark Jena, 2019).

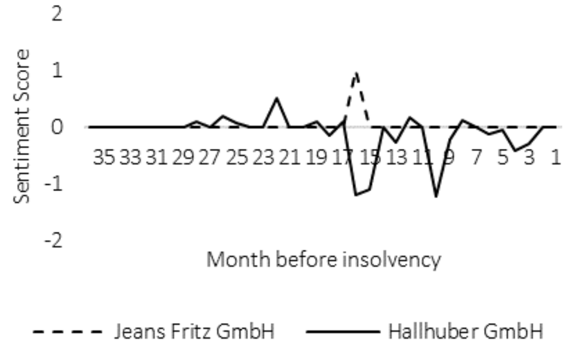

Figure 2: Monthly sentiment scores for Jeans Fritz GmbH and Hallhuber GmbH

The sentiment scores for the company pairs pictured in Figure 3 and Figure 4 are similar. Whereas the solvent companies show only positive sentiment, solely Tweets with negative sentiment are posted in the three years before the insolvencies.

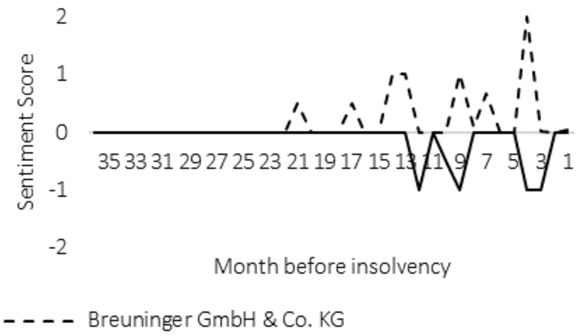

Figure 3: Monthly sentiment scores for Breuninger GmbH & Co. KG and Galeria Kaufhof GmbH

Tweets before the insolvency of Galeria Kaufhof GmbH are dominated by statements concerning strikes of employees and downsizing (Händlerbund, 2019; NTV, 2019). On the other hand, Breuninger GmbH & Co. KG is growing and establishing new jobs (N-News, 2019).

Engelhorn GmbH & Co. KGaA, that is in the group of financially stable companies, launched a new E-Commerce-platform, which results in positive sentiment (Tradebyte, 2019). Especially during the lockdowns of the corona-pandemic, E-Commerce-platforms were necessary in order to be able to generate turnover. However, for the Bonita GmbH neutral content was posted among news about a potential divestment and the reduction of governmental sureties leading to the insolvency (Kapalschinski, 2020).

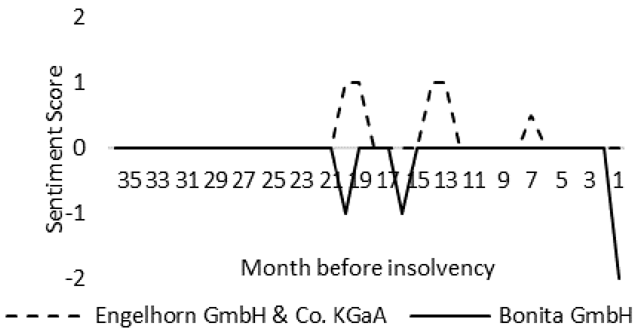

Figure 4: Monthly sentiment scores for Engelhorn GmbH & Co. KGaA and Bonita GmbH

Negative Tweets with information about the closing of stores and financial struggles dominated the UGC three years before the insolvency of Esprit Holding Limited (Lindner, 2019). Nevertheless, in Figure 5 it can be seen that shortly before the insolvency, positive content was published. This encompasses a statement about the launch of a new E-Commerce-platform which, in contrast to the platform launched by Engelhorn GmbH & Co. KGaA, could not prevent the bankruptcy (Textilwirtschaft, 2020).

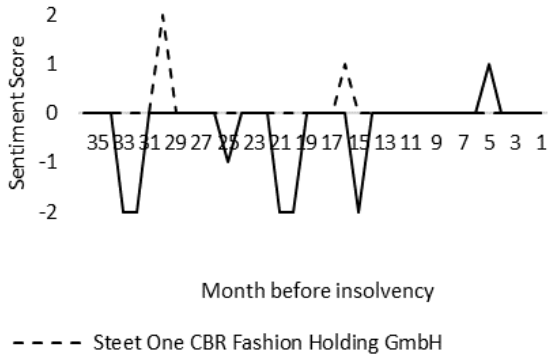

Figure 5: Monthly sentiment scores for Street One CBR Fashion Holding GmbH and Esprit Holding Limited

In Figure 6, the negative sentiment scores in the nine months before the insolvency of the Veritas AG are caused by reports about manpower reduction and the necessity of investors due to financial struggles (HV-Besuch, 2020). Beforehand and for the solvent counterpart the scores are neutral.

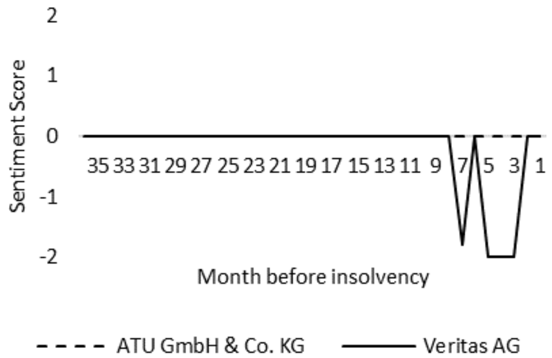

Figure 6: Monthly sentiment scores for ATU GmbH & Co. KG and Veritas AG

Before the insolvency of the KSM Casting Group GmbH, the sentiment graph does not imply a future insolvency. Although 31 months before the insolvency a Tweet in which a strike is communicated was issued, only positive sentiment concerning a sustainable, climate protecting alignment of the company can be identified as seen in Figure 7 (Forum Wermelskirchen, 2018; Nachhaltigkeitskodex, 2019).

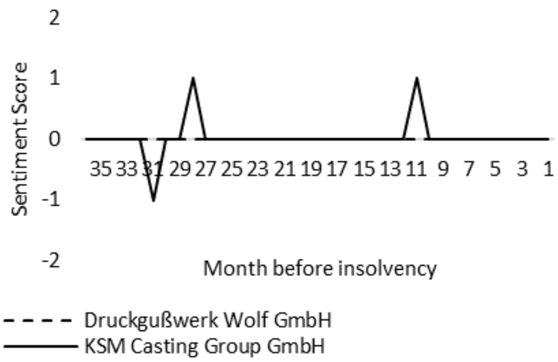

Figure 7: Monthly sentiment scores for Druckgußwerk Wolf GmbH and KSM Casting Group GmbH

Figure 8 shows only neutral sentiment with the exception of one positive score resulting from a Tweet in which an acquisition by the solvent company Stölting Service Group GmbH is discussed (audium capital partners, 2019).

The two remaining pairs of companies consisting of the Tria Personal GmbH, ZAG GmbH as well as ARWE Holding GmbH and Mr. Wash Autoservice AG show only neutral sentiment. Due to the limited added value these graphs are not depicted here.

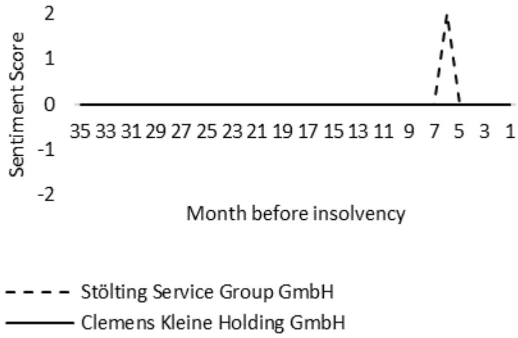

Figure 8: Monthly sentiment scores for Stölting Service Group GmbH and Clemens Kleine Holding GmbH

In general, the descriptive statistics from our sample indicate, that negative sentiment can be detected before an insolvency predominantly. Still, negative Tweets were obtained for financially stable companies. Thus, negative posts should be examined carefully before denying credit. Topics that were discussed solely before insolvencies include downsizing, strikes and financial struggles (e. g. the necessity of investors). When these topics occur related to a company, the validity and potential impact on credit decisions should be analyzed in order to prevent potential losses due to credit default.

4.3 Hypotheses testing and verification of the descriptive results through quantitative statistics

H1 *(The amount of UGC during the corona-pandemic is greater before an insolvency of a company than for financially stable companies)* is tested by application of an independent T-Test because the data is not related to dependent samples. A precondition for the T-Test is a normal distribution of the data which can be verified by application of the Kolmogorov-Smirnov-Test or the Shapiro-Wilk-Test (Field, 2009).

Table 4: P-values from Tests for normal distribution of the number of Tweets

	Significance-Level	
	Kolmogorov-Smirnov-Test	Shapiro-Wilk-Test
Insolvent companies	0,04	<0,01
Solvent Companies	<0,01	<0,01

The results in Table 4 show, that the data is not normally distributed because all p-values are below the threshold of 0,05 (Field, 2009). Therefore, it is not possible to draw conclusions with statistical significance regarding differences in the number of Tweets for both groups and H1 cannot be investigated any further.

Results from Mengelkamp, Hobert and Schumann (2015a) which showed, that the number of Tweets differs between solvent and insolvent companies, can therefore not be confirmed in order to generate added value for corporate credit decisions during times with severe governmental restrictions (e. g. a lockdown during a pandemic) by our data set.

We verified H2 (*The sentiment of UGC during the corona-pandemic is worse before an insolvency of a company than for financially stable companies)* likewise. Nevertheless, instead of the number of Tweets for both groups, we compared the sentiment scores of the Tweets regarding solvent and insolvent companies. Since our sample consists of 1009 Tweets, we can assume normal distribution due to the central limit theorem (Field, 2009). Thus, we immediately applied the T-Test whose p-value is <0,01*** and therefore we can confirm H2 on all established levels of significance (Field, 2009). The result indicates, that the sentiment before a corporate insolvency is significantly worse when compared to sentiment from UGC of solvent counterparts in the same time span. Results from Mengelkamp, Hobert and Schumann (2015a) can therefore be confirmed during extraordinary economic circumstances which are manifested by a pandemic in our data set.

H3 (*It is possible to distinguish between solvent and insolvent companies based on sentiment scores derived from textual UGC during the corona-pandemic)* is evaluated by application of the k-nearest-neighbor algorithm. This algorithm has been widely used in the domain of credit risk assessment especially with the purpose of classification between potentially solvent and insolvent companies (Mengelkamp et al., 2015a; Olson & Wu, 2008). We applied the k-nearest-neighbor algorithm to the monthly aggregated sentiment scores in accordance with Mengelkamp, Hobert and Schumann (2015a). Hereby, the scores of the six months before the insolvencies are used as input in the first iteration. Then, the algorithm is provided with data from the months two until seven before the insolvency. The time window of six months is then shifted backwards in order to analyze in how far the sentiment scores in time spans way ahead the date of insolvency contain relevant information based on which credit decisions can be made. The results in Figure 9 show, that the classification accuracy is 70% in the nine months before the insolvencies. Then, it deceases to 65% for the next two six-months-windows and consecutively is lowered to 60%. The classification accuracy stays at 60% except for the time windows in the months 11-16, 13-18 and 14-19 in which it is only 55%. For the months 18-23 or longer before the insolvencies, the k-nearest-neighbor algorithm caused an error. The error occurred because the sentiment scores for some months did not differ between the training and test data sets. Thus, a classification based on sentiment scores which are calculated based on UGC with more than 22 months before the insolvencies is not possible.

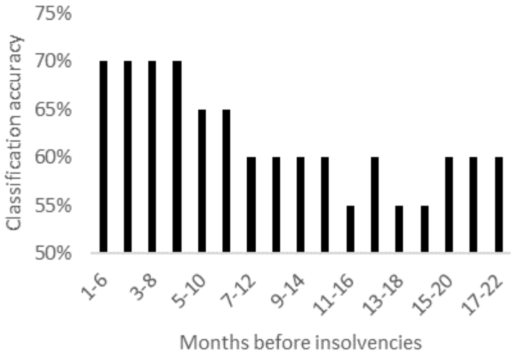

Figure 9: Classification accuracy of the k-nearest-neighbor algorithm based on monthly aggregated sentiment scores

Our results differ from findings obtained by Mengelkamp, Hobert and Schumann (2015a) in some aspects. At first, our maximum classification accuracy with 70% is lower. While analyzing the ten biggest corporate insolvencies of 2013 and solvent counterparts, Mengelkamp, Hobert and Schumann (2015a) were able to achieve a classification accuracy of 75% when data issued in the six months before the insolvencies was analyzed. Then, the classification accuracies dropped to 65% in the months 2-7 and went back up to 70% in the months 3-8 before the insolvencies whereby our classification accuracies are stable at 70% for the first nine months before the dates of insolvency. Our study provides added value because it shows, that the classification accuracy is mostly steady at 60% until 22 months before the insolvencies during the corona-pandemic, in which UGC is especially important for corporate credit risk assessment, whereby timeframes which consider only up to 13 months have been analyzed in previous literature (Mengelkamp et al., 2015a).

5. Discussion

Our findings indicate, that an increasing number of Tweets is not as appropriate as stated in previous research when it is used to assess the creditworthiness of a company, although our descriptive findings support the thesis (Mengelkamp, Hobert and Schumann, 2015). H1, which stated that the number of Tweets is significantly higher for the group of insolvent companies, could not be confirmed in contrast to previous studies (Mengelkamp, Hobert and Schumann, 2015). The validation of H2 supports previous findings. It can be confirmed based on our data set, that the sentiment before a corporate insolvency is significantly lower than for a group consisting of financially stable companies. The importance of sentiment scores for corporate credit risk analysis is therefore solidified.

In addition to that, results from the application of the k-nearest-neighbor algorithm support H3, which further emphasizes the importance to integrate the examination of UGC in corporate credit decisions processes. The classification accuracy is above 50%, which represents a random classification. in all covered months in which the k-nearest-neighbor algorithm was able to be executed without an error. Thus, practitioners and scientists can assume, that negative sentiment and especially a shift from positive to negative sentiment is an indicator for an impeding insolvency.

Still, the literature base for this field of application is improvable. Our data set does not overcome all limits of previous studies for example regarding sample size, different industries and varying forms and sizes of companies (Mengelkamp et al., 2015a).

6. Concluding Comments

Further research is needed in order to clarify the validity of the amount of UGC as an indicator for future corporate insolvencies. Next to that, larger data sets with companies varying e. g. in size, legal form and industry should be analyzed. In addition to that, the research should be expanded to other social media platforms in order to evaluate their potential to provide additional information based on which the information asymmetry in principal-agents-relationships in the domain of credit assessment can be reduced. Methods, which are used to verify the authenticity of the content should also be developed.

Lastly, tools by which the UGC is automatically analyzed e. g. by use of machine learning algorithms and presented to credit decision makers, should be implemented and evaluated.

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